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14. ABSTRACT For this project, we have primarily addressed problem of wireless coverage using a team of mobile robots with ad-hoc communications through the development of distributed probabilistic coordination models and algorithms. For coverage, a team of mobile robots, each with limited sensing and communications ranges, must provide a set of communication chains that cover as large a space as possible. Our goal was to develop robot coordination algorithms that perform communications chaining accurately and robustly in the face of various uncertainty factors, such as noise in sensing and wireless signal						
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Final Report for AFOSR Grant FA9550-09-1-0206

“Coordinating Robotic Networks Through Belief Propagation” Prof. Odest Chadwicke Jenkins, Brown University

Introduction

For this project, we have primarily addressed the problem of wireless coverage using a team of mobile robots with ad-hoc communications through the development of distributed probabilistic coordination models and algorithms. For coverage, a team of mobile robots, each with limited sensing and communications ranges, must provide a set of communication chains that cover as large a space as possible. Our goal was to develop robot coordination algorithms that perform communications chaining accurately and robustly in the face of various uncertainty factors, such as noise in sensing and wireless signal strength, with secondary consideration of constrained resources, such as power, computation, and communications bandwidth. We proposed and developed robot software to reach this goal based on the Markov Random Fields (MRFs) as a probabilistic model for distributed inference. The Multi-robot Markov Random Field model (described in [1] and [2]) allowed us to unify existing algorithms for multi-robot coordination, such as the commonly used potential field, in a generative model and propose new coordination algorithms using belief propagation. Based on this model, we produced a plug-and-play software framework for distributed multi-robot coordination on top of the Robot Operating System (ROS). This framework [3] enabled empirical comparison of belief propagation coordination against baseline algorithms (such the potential field) in various environments, both simulated and with real robots. We additionally explored using this same MRF model for coordination problems over other forms of complex networks, where global solutions result from local coordination. Specifically in the area of manifold learning, we used a MRF-based model to develop BP-Isomap, a belief propagation version of Isomap nonlinearity dimension reduction. BP-Isomap [4] probabilistically extended manifold learning towards greater robustness to noise in neighborhood selection. This work has also contributed software packages for reinforcement learning using ROS with an eye to distributed coordination using graph Laplacians [5].

Multi-robot Markov Random Fields

An MRF is a graphical model that factors a system into a finite set of observed and hidden, or latent, variables with pairwise interactions between them. Variables in our case are vector-valued random variables, meaning that they are multidimensional probability distributions. Each agent i maintains one observed and one hidden variable. The observed variable y_i represents an agent's perception of the physical world. These perceptions are derived from a robot's own sensing information and pertain only to information about physical objects in the world. Local evidence only includes information about other agents in a mechanical sense; it does not contain any information about their beliefs or intentions. The state, which is represented by the hidden variable x_i , is a vector consisting of variables important to the agent's behavior. The state vector can contain variables representing intended actions for the agent, plans for other agents, knowledge about the environment (such as localization information or object classification), or other high level information.

In the multi-robot case, the state of an agent is conditional on its observed variable and the states of other agents whose states it can perceive. From the perspective of a single agent, the other nodes are actually the perceived states of other agents. Because we are concerned with collaboration between cooperative agents, there is no reason for agents to deceive each other and any information about state can be explicitly communicated. Considering state to be perceived state will simplify the model and allow us to model a collaborative team as a single graph with agents mutually affecting each other (Figure 1). Given the observed and hidden variables, a pairwise MRF factors inference of a collaborative team action x into two functions:

pairwise compatibility $\psi_{j,i}(x_j, x_i)$ between each agent pair (i,j) and local evidence $\phi_i(x_i, y_i)$.

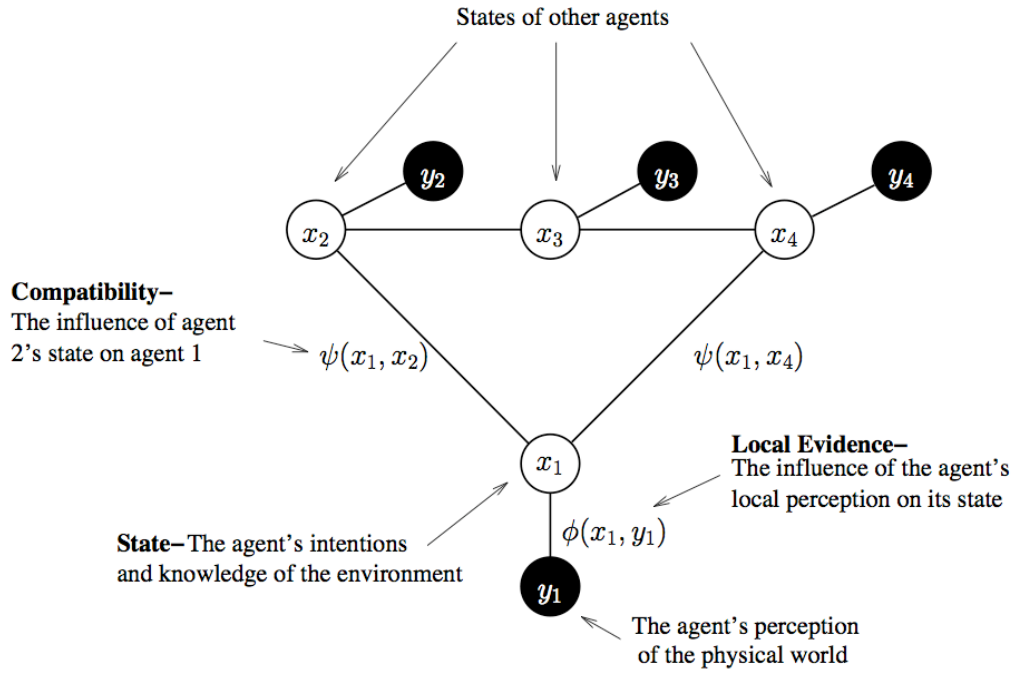


Figure 1: The Multi-robot Markov Random Field model for representing the coordination of multiple agents, with latent beliefs x_i about the team's actions, from the local observations of individual robots y_i .

Multi-robot ROS software framework

For implementation of the Multi-Robot Markov Random Field, we have produced: 1) a plug-and-play framework for multi-robot coordination algorithms with existing robot middleware and mesh network packages and 2) a low-cost implementation of the proposed framework using commercial off-the-shelf hardware and open-source software. Our framework supports multi-robot coordination through a mesh network which allows robots to communicate information with local neighbors to produce desired global behavior. We have used an implementation of the proposed framework to conduct experiments in static unmapped physical environments both indoors and outdoors. Our implementation of the proposed framework is available to the community as an experimental resource. Our aim is that by providing these systems other groups can leverage our work to test their own complex network systems and algorithms in the physical world. This framework has been released as open-source through the Brown University ROS repository, `brown-ros-pkg` (<http://code.google.com/p/brown-ros-pkg/>).

Initially released as the `meshnet` ROS package, we implemented mesh networking capabilities for multi-robot systems, enabling autonomous coordination and remote user control over mobile ad hoc networks. This work combined the ROS robot middleware framework (<http://ros.org>) and B.A.T.M.A.N., an *ad hoc* routing protocol (<http://www.open-mesh.net/>), with custom data channeling code. This meshnet package was later modified to use OLSR (<http://www.olsr.org/>), which proved to provide a better interface for mesh networking capability. Illustrated in Figure 2, an initial 3-robot test for teleoperation and video forwarding through the robot mesh network can be viewed online at <http://www.flickr.com/photos/brownrobotics/4604930112/>.



Figure 2: Snapshot sequences from 3-robot mobile mesh network test. (Left) the teleoperator at the base station controls a lead robot to explore an office environment (right) using video from its camera. (Middle) intermediate robot nodes connect the lead robot to the base station when they are outside direct communications range.

Building on this meshnet, we were able to implement standard potential field coordination for decentralized robot coverage scenarios. Highlighted in Figure 3, the system was able to perform wireless coverage for situations with up to 8 commodity off-the-shelf robots over larger areas than typical robot coordination research using only wireless signal strength for sensing. Using the publish-subscribe messaging of ROS, a multi-robot coordination algorithm can interface with and run on multi-robot platforms by subscribing to appropriate input topics (e.g., robot pose, wifi signal strength) and publishing appropriate output topics (e.g., robot movement commands). Support packages in ROS and OLSR handle interfacing with robot hardware and mesh network, respectively, providing an abstraction layer for coordination algorithms.



Figure 3: Robots in our team consist of off-the-shelf iRobot Create with a commodity netbook (left). Using only signal strength for measurement, coordination occurs over ac hoc networks to cover larger spaces, such as the 3rd Floor of the Brown CIT building (middle, right).

Released as part of the Coordinating Robot Networks using Belief Propagation (crnbp) ROS package, we extended our meshnet robot coordination framework to faithfully represent and provide comparisons for belief propagation with Multi-robot Markov Random Fields. This package provides autonomous localization for each robot (using particle filtering on a known map) and belief propagation modules for autonomous coordination. Localization modules provide belief distributions about the location of a robot in the environment based on its local sensing and wireless signal strength to other robots. These distributions over location inform the inference over coordination, resulting in distributions for the desired location of each robot for coverage. Estimates are taken from target location distributions to generate and update motor plans for each robot. Shown in Figure 4, we have tested the crnbp package with robot teams of up to 22 robots, including the iRobot Create-based mobility platform (shown in

Figure 2) as well as the AR.Drone quadrotor helicopter (released as through our ardrone_brown and ardrone_nav ROS packages).

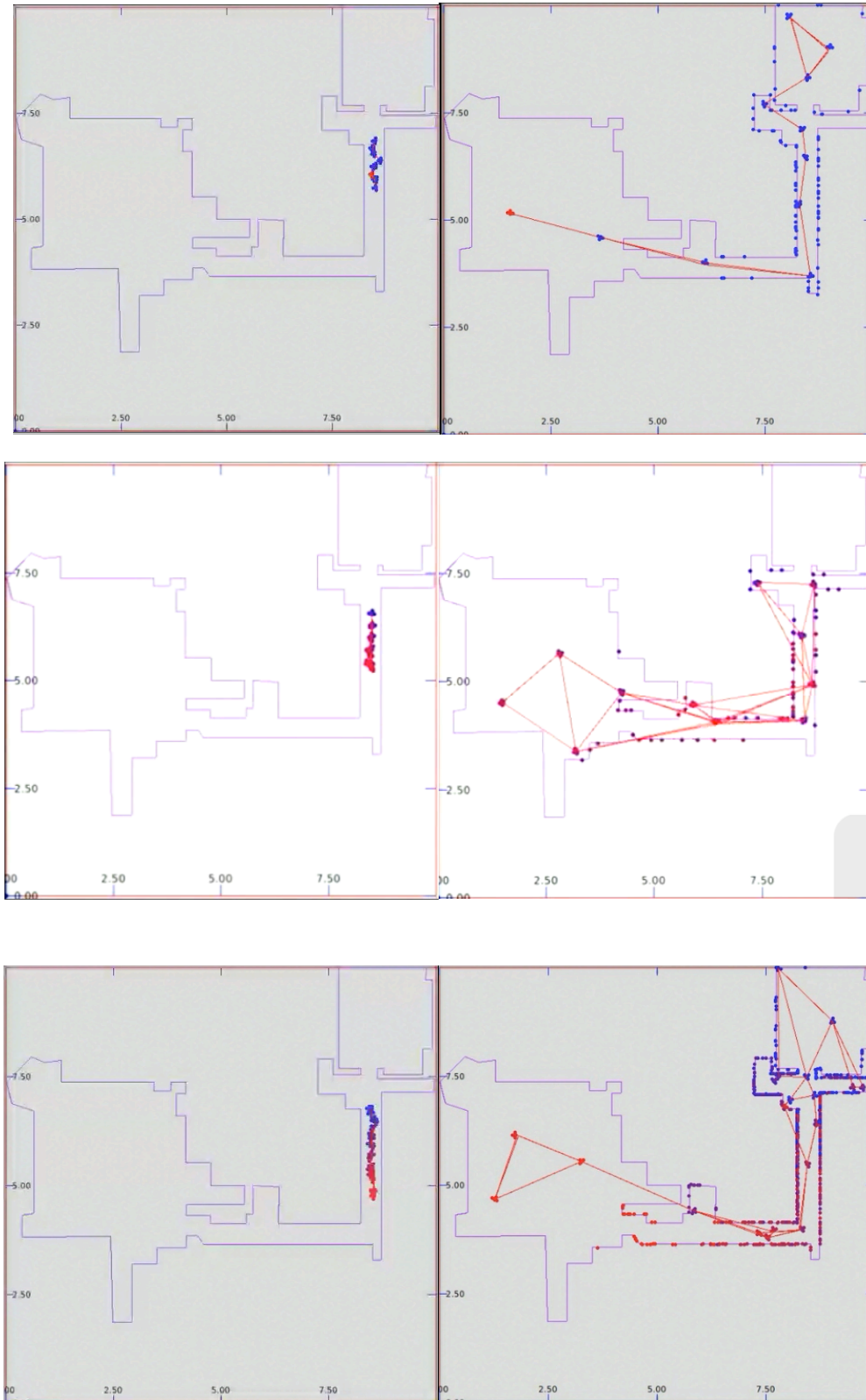


Figure 4: Results from crnbp wireless coverage with teams of 11 (top row), 15 (middle row), and 22 (bottom row) robots on the first floor of the Brown CIT building. Each row shows the starting and converged team configurations. Each picture displays the locations of each robot with edges showing robots that communicating.

Summary

For this project, we have produced the Multi-robot Markov Random Field as a unifying model for multi-robot coordination algorithms. This model allows for the creation and comparison of multi-robot coordination algorithms in a generative framework for expression of (but not limited to) probabilistic inference. We have proposed coordination algorithms using probabilistic belief propagation to improve robustness in the face of perceptual uncertainty. Our algorithms have been implemented and released open-source through the ROS robot middleware framework.

References

- [1] J. Butterfield, B. Gerkey, and O. Jenkins. Multi-robot Markov Random Fields. In Autonomous Agents and Multi Agent Systems (AAMAS 2008), pages 1211-1214, Estoril, Portugal, May 2008.
- [2] J. Butterfield, O. C. Jenkins, D. Sobel, and J. Schwertfeger. Modeling aspects of Theory of Mind with Markov Random Fields. *International Journal of Social Robotics*, 1(1):41-51, Jan 2009.
- [3] A. Tsoli, O.C. Jenkins, "A plug-and-play framework for decentralized multi-robot coordination using commodity robot platforms", Brown CS technical report.
- [4] A. Tsoli and O. C. Jenkins, "Neighborhood denoising for learning high-dimensional grasping manifolds," in *International Conference on Intelligent Robots and Systems (IROS 2008)*, Nice, France, 2008, pp. 3680-3685.
- [5] Sarah Osentoski and Sridhar Mahadevan, Basis Function Construction for Hierarchical Reinforcement Learning, Ninth International Conference on Autonomous Agents and Multiagent Systems (AAMAS), Toronto, Canada, May 2010

Software Releases

The following software packages resulting from this work have been released open-source for use with ROS, the Robot Operating System:

- `ardrone_brown`: driver for Parrot AR.Drone quadrotor helicopter
 - (http://brown-ros-pkg.googlecode.com/svn/trunk/experimental/ardrone_brown/)
- `ardrone_nav`: autonomous quadrotor navigation
 - (http://brown-ros-pkg.googlecode.com/svn/trunk/experimental/ardrone_nav/)
- `crnbp`: Coordinating Robot Networks with Belief Propagation ROS framework
 - (<http://brown-ros-pkg.googlecode.com/svn/trunk/experimental/crnbp/>)
- `rl_glue`: ROS framework for RL-Glue reinforcement learning
 - (<http://brown-ros-pkg.googlecode.com/svn/trunk/experimental/rlrobot/>)
- `meshnet`: multi-robot coordination framework using BATMAN and OLSR
 - deprecated due to `crnbp`
 - (<http://brown-ros-pkg.googlecode.com/svn/trunk/experimental/meshnet/>)